(Slide 1)  
Hi. My name is Hyosang Yoon and I am a first-year graduate student working with professor Kerri Cahoy. I am going to present my research about “Star-Pattern Identification using a correlation approach”.

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The outline of my talk will first be an introduction which covers the motivation and background literature. Then I will describe my approach to this problem. I will then present the results and conclusions.

(Slide 3)  
Introduction. A star sensor is one of the most accurate attitude sensors for spacecraft. It estimates a spacecraft’s attitude from images of star patterns.  
(Click) This is a picture of a typical star sensor. It looks like a camera, and it is a camera.

(Click) It takes a picture of stars

(Click) and the image will look like this.

(Click) The star sensor will recognize these stars

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Star identification is a process to match the imaged stars to a star catalogue. Once you have the star image like this

(Click) You do not know which stars these are.

(Click) By star identification which means matching the star pattern to the catalogue,

(Click) You will have their ID numbers and their positions from a star catalogue.

(Click) Then, you can estimate the attitude.

(Laser Pointer) My project focused on this step.

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Now, I will talk about the motivation and the objective of my research. There is a problem with using star sensors in a dynamic environment. A star sensor needs a certain time to integrate star light. If a spacecraft is rotating, the star image will be blurred. These pictures show the blurring. In addition, there would also be background noise. Because of both blurring and noise, it may be hard to determine the center position of this star. This increases star centroiding error and some weak stars will disappear on the image.

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So, I set my research goal to make a robust star identification algorithm for a dynamic environment. “Robust” means that it is possible to identify stars in the presence of noise and errors. There were two requirements for the algorithm. First, the algorithm shall work without preliminary attitude information. In other words, the sensor should be able to give attitude from a single image. Also, the algorithm shall be robust to centroid error, missing stars and false-positives.

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There are several previous researches for star identification algorithms. They can be categorized into roughly two groups – Subgraph Isomorphism and Pattern Recognition.

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Basically, subgraph isomorphism compares angular distance and geometric figures such as triangles that consist of stars. It finds the intersection pairs for each angular distance from pre-constructed star-pair catalog.

Pattern recognition regards a star image as a 2D image and generate 2D discrete pattern from it. Then, it finds the most similar pattern from onboard database.

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This is the comparison of the two groups. They have almost opposite characteristics. Pattern recognition is more robust to centroiding error, or star position error, while Subgraph Isomorphism is better for missing stars and false positives.

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(continued from the previous slide) The differences are from their methodologies. Subgraph isomorphism uses angular distance directly to select the candidate star-pairs. This is a strong point that enables the identification with a small number of stars. However, the absence of metrics makes it vulnerable to centroiding error because without some metrics, it is hard to resolve ambiguity between several possible solutions.

Unlike subgraph isomorphism, pattern recognition uses metrics that represent similarity of two patterns. But it uses angular distance between stars only to make a discrete pattern. This means pattern recognition is less sensitive or robust to centroiding error. However, it also means it needs larger numbers of stars. Another drawback is the arrangement process of stars to fit in a 2D frame

So, my question was, can I combine two advantages?

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From this slide, I will talk about my approach to this problem. I decided to use pattern recognition technique, but I tried to combine the advantages of subgraph isomorphism by using stars’ relative positions directly to calculate the metrics in continuous domain. Also, I tried to resolve the problem with arrangement by pre-defined reference stars by NOT using pre-constructed star-pattern database for each star.

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From this slide, I will get into my approach in details. This work has been published in these two references. To construct star pattern model, I asked a fundamental question. What does it mean to say that the i-th star’s center is located at (xi, yi)?

My answer to this question is that “The probability of the i-th star being located at (xi, yi) is high”. So, I modeled the location of stars as a normally distributed PDF.

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If I describe it in mathematical formula, the PDF becomes this. xn yn is the coordinate of the n-th star centroid, sigma square is the variance of centroiding error, which depends on the optics’ performance. A0 is the height of the curve and it is negligible for relative comparison.

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For metrics to compare, I asked another fundamental question. “What are the best metrics to represent the similarity of two functions?” There is an empirical answer, which is correlation. 2 dimensional correlation is generally given in this form. A is original image on the CCD and B is the similar image in the star catalog.

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So, I chose the correlation as the score function. The full formula is like this. It defines metrics to compare in continuous domain unlike previous discrete pattern. This equation seems to be difficult to solve since it has double integrals, sigmas and exponentials of squares.

However, we can just take advantage of Fourier transformation. According to the cross-correlation theorem, the correlation becomes just multiplication in frequency domain.

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After some calculation, we can derive the score function as this. This form is very suitable for onboard calculation. This score function provides continuous metrics and it uses the angular distance explicitly. However, the arrangement problem for 2D pattern still exists.

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Now, I will talk about vector pattern matching. First, Stars are on the celestial sphere, which is 3D space, not 2D plane. Each star can be modeled as a unit vector and it is a point on a sphere of radius 1.

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In the vector pattern matching, the arrangement process uses any two-star pair as the reference. Once we select a reference pair in the star image, we can select candidate pairs from the pair catalog. Then, rotate star vector patterns so that the reference pair is superimposed on the candidate pair and calculate the score function. This eliminates the problem caused by arrangement with the closest star.

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For these star models, the mathematic model and the score function becomes like this. This RRk is the arc length between R and Rk. The score function is modified with the arc length. This integral is over the sphere surface, so it is hard to get an exact solution.

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Similar to the previous, we can derive the score function as this. For convenience in calculation, we can neglect the common part as this. This is the new score function for my algorithm.

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I now present the results. I conducted monte-carlo simulation to verify the performance of the algorithm. This is the condition of the simulation. The onboard star catalog has 4975 stars where the minimum magnitude of stars is 5.5. I added star centroiding error from 0 to 60 arcsecond, and put 0 to 3 false positives. 10,000 simulations were conducted for each condition. The result was compared to two other algorithms. These two are popular algorithms from each category.

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The main metrics for performance is identification rate. It is the percentage of successful identification out of total simulation. The criterion of success is that more than 2 stars identified correctly without any misidentified stars.

Also, there are other metrics to look at for applications. Memory usage and processing time are sometimes considerable for embedded systems.

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In case 1, here (1st plot) the star pattern is identical to that of the star catalog. In plot 2, 3, 4, there is 1, 2, and 3 false positive added to the image. This result shows the pros and cons of the two categories clearly. The subgraph isomorphism is robust to false positives and the pattern matching is robust to position error. The new algorithm demonstrate the best robustness to both false positives and centroiding error.

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In case 2, the detection power is less resulting in missing stars compared to star catalog. The results showed that my algorithm gave the accurate performance compared to the algorithms from the other two categories.

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In case 3, more stars appeared on the image than the onboard star catalog. The stars not included in the onboard star catalog are just false positives for the star sensor. In this case, the new algorithm showed consistently high performance while the others showed significantly decreased performance.

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Conclusions. I developed a star identification algorithm which is robust to centroiding error, missing stars, and false positives. This algorithm has two good properties. The performance has been verified by numerous Monte-Carlo simulations.

However, the algorithm does have some drawbacks. It is more complicated than the others since it goes through the processes from the both categories. Also, it uses more memory than traditional pattern matching algorithms. The identification time is the biggest drawback of this algorithm. The identification time is greater than twice that of the modified grid algorithm and the pyramid algorithm. This is because the calculation of an exponential in the score function takes more time.

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For future study, the most pressing issue is to reduce the identification time. It can be done by optimization of the exponential calculation. Also, I want to find a method to calculate the correlation in frequency domain, like correlation pattern matching technique in image processing. If I can find a method to take Fourier transform on a sphere’s surface, we can find the best-fit position of the imaged star pattern in the celestial sphere in frequency domain. This will dramatically reduce the complexity of the algorithm as well as the identification time.